Cascading Innovation*

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Abstract

US government spending since World War II has been characterized by large investments in defense-related high-tech goods and services and R&D. In turn, this means that the Department of Defense (DoD) has had a large role in funding corporate innovation in the US. This paper (i) quantifies the impact of military procurement spending on corporate innovation by publicly listed firms and (ii) shows that DoD impact on innovation was not limited to the winners of defense contracts but instead cascaded through the supply chain of DoD contractors via indirect market size effects, working through firm-to-firm input linkages. We use a database of detailed, historical procurement contracts for all Department of Defense (DoD) prime contracts since 1966. Product-level spending shifts are used as a source of exogenous variation in firm-level procurement receipts. We combine this data with information on the supply chain linkages of publicly listed firms. Our estimates indicate that defense procurement has a positive direct impact on patenting and R&D investment, with an elasticity of approximately 0.07 across both measures of innovation for DoD contractors. Further, our estimates imply that the derived demand for inputs following the award of a DoD contract constitutes a large indirect market size effect for the suppliers of DoD contractors. These indirect market size effects in turn induce innovation cascades working up the supply chain. We find that the elasticity of innovation outcomes to indirect DoD market size shocks is about half of that estimated for direct contractors but affects a much larger number of firms, increasing the effect of defense spending on aggregate innovation by at least 20%.

Keywords: Induced Innovation, Patenting, R&D, Defense Spending, Production Networks

Preliminary and incomplete.
Please do not circulate.

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1 Introduction

The seminal observation that "the amount of invention is governed by the extent of the market" (Schmookler, 1966) has since spawned a large literature exploring the role of economic profit and 'demand-pull' influences on the pattern of invention, with a special conceptual emphasis on the effects of market size. This agenda for studying technical change has been followed up heavily in empirical research appearing over the last 15-20 years. Invariably, this research has focused on isolating market size effects in technology-rich final goods alone, such as drugs and vaccines.

In doing so, this literature has overlooked the possibility that market size effects may reverberate through the supply chain and have spillover effects on innovation outcomes for direct (and indirect) suppliers of final goods firms. The rationale for this unexplored possibility is clear: following an increase in the extent of the final goods market, final goods producers will likely increase their demand for intermediate inputs. This implies a larger market size for intermediate input suppliers, thus opening the door for cascading market size effects and rendering innovation more profitable throughout the supply chain. If such innovation cascades are indeed operative in the economy, this in turn implies that focusing the analysis on final goods markets alone will understate the role of market size effects on innovation.

In this paper, we investigate the presence and significance of such innovation cascades following final goods' market size increases. We do so by studying the propagation of U.S. military spending shocks through production networks over time. Specifically, we trace how shifts in spending by the U.S. Department of Defense first affect innovation decisions by their main contractors and, in turn, how these determine innovation outcomes throughout the supplier network of these contractors. Our estimates indicate that defense procurement has a positive direct impact on patenting and R&D investment, with an elasticity of approximately 0.07 across both measures of innovation for military contractors. Further, our estimates imply that the derived demand for inputs following the award of a defense contract constitutes a large indirect market size effect for the suppliers of such military contractors. These indirect market size effects then induce innovation cascades working up the supply chain.

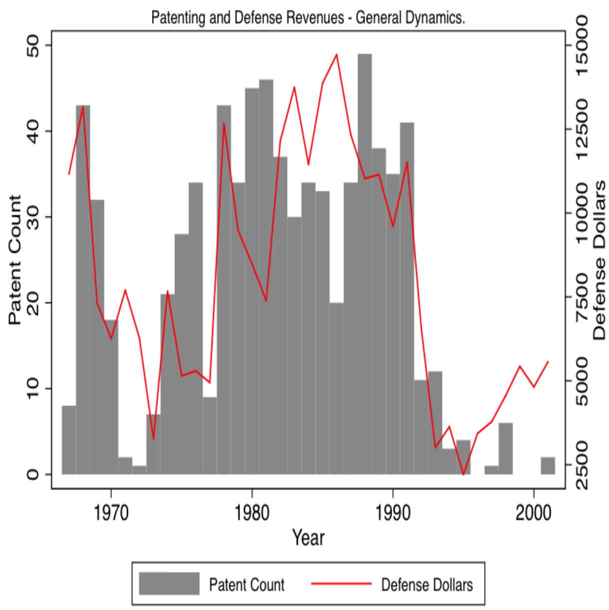
Our focus on military spending is justified by the outsized role of the U.S. Department of Defense (DoD) in driving U.S. innovation investments since World War II. The NSF(2006) estimates that DoD funding accounts for around 20% of R&D expenditures in the post-war period, with a peak of around 30% in the late 1950s and early 1960s. Furthermore, the amount of money flowing into high-tech, defense-focused production dwarfs the amount spent on other prominent innovation policy tools. For example, the Federal R&D tax credit costs around \$6.5 billion per year while support for basic science through the National Science Foundation figures at \$7 billion (NSF 2006). By contrast, around \$16 billion per year is spent on military R&D procurement alone, along with another \$40-50 billion in spending on high-tech products. This makes defense spending – and military procurement in particular – one of the most significant topics for the study of induced innovation in the US economy.

To guide our empirical analysis, we begin by making explicit our key theoretical point that market size increases at the final demand stage will have two effects on firm-level innovation. First, by increasing profit opportunities for final demand firms, it will spur (costly) innovation activities by these firms. This is the traditional market size effect, whereby enlarging the extent of the market, renders final goods firms larger, more profitable and more innovative. However, this market size increase will also have a second, novel, effect. In particular, we show that this final demand pull will cascade through the supply chain in a series of recursive market size effects. To see this, note that a final demand increase for a given variety or final goods firm (such as the ones supplying the DoD) translates into an increase in derived demand for intermediate inputs by this firm. Thus, given that the market size of intermediate input suppliers is given by the derived demand from their customers (i.e. the final goods firms), an increase in the latter will work as a traditional market size effect, rendering upstream suppliers larger, more profitable and more innovative.

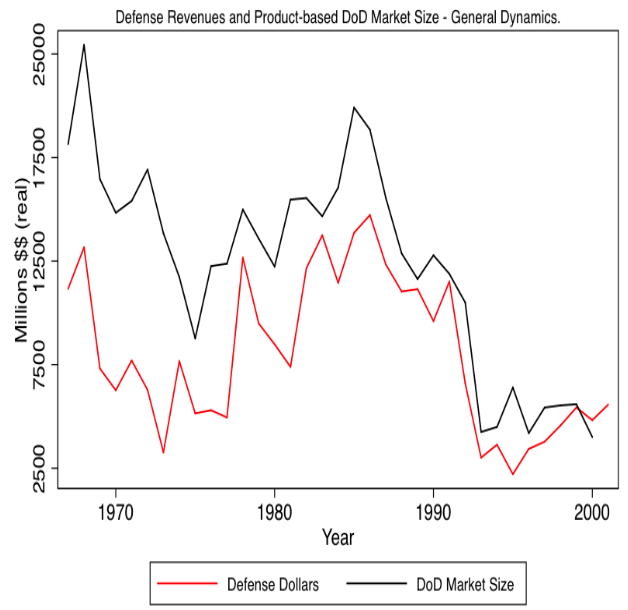
Proceeding to our empirical analysis, our strategy leverages very detailed data on defense contracts over time which allows us to define a novel, firm-specific measure of DoD-related market size. The key feature we exploit is the DoD's Federal Supply Code (FSC) system of product codes, which offers a consistent breakdown of DoD spending since 1966. We use this to measure how compositional shifts in aggregate DoD spending affect contracting firms' sales opportunities. Moreover, we then track how these shifts in market size at the major contractor level then affect market size for firms further down the supply chain. By tracing these effects down the supply chain we are therefore able to limit concerns about the potential endogeneity of DoD allocation decisions amongst the 'first round' contractors.

As a way illustrating the nature of this strategy, Figure 1 presents information on General Dynamics, a major DoD contractor, famous for producing the F-16 Fighting Falcon aircraft, the Stinger surface-to-air missile systems or the M1 Abrams tank. Using the information on DoD procurement contracts, Figure 1a shows General Dynamics as a major defense contractor throughout the 1980s. By merging in Compustat's balance sheet information on General Dynamics as well as NBER patent data we are able to inspect firm-level innovation outcomes – such as R&D expenditures and patents – following the award of DoD contracts. In particular, Figure 1a depicts the number of patents filed by General Dynamics alongside the total dollar amount of DoD contracts being awarded every year. Clearly, the two measures comove.

The concern is, of course, that of reverse causality whereby General Dynamics' innovation efforts lead to the award of DoD procurement contracts, rather than reverse. To address these concerns, we propose an instrumental variables strategy which leverages from the detailed product coding by the Department of Defense. In particular, the data allows us to construct, for each firm, a measure of product market specialization. Lagging this measure – in order to limit anticipation effects – and interacting it with current DoD spending in detailed product categories, gives us a proxy for the potential firm-specific market size of defense contracts.



(a) Defense Contracts Awarded and Patents Filed by General Dynamics



(b) Defense Contracts Awarded and Potential Market Size for General Dynamics

Notes: The left panel of the figure depicts the total value of DoD contracts awarded to General Dynamics alongside the number of patents filed by this firm from 1965-2005. The right panel depicts the same measure of contracts awarded alongside our measure of potential market size for General Dynamics. *Source:* DoD Procurement Records and NBER Patent Database.

Note that this measure varies over time, depending on the lagged specialization patterns of the firm and compositional shifts in DoD spending over the years. Figure 1b depicts the resulting potential market size measure for General Dynamics. In our main regressions, we use this instrumentation strategy in order to assess the impact of DoD contracting on innovation outcomes at the firm level.

To understand how we look at innovation outcomes across the supply chain note that, according to the Financial Accounting Standards Rule No.131, publicly listed firms are required to disclose the identity of their major customers. This information can be sourced from Compustat's Customer Segment file in order to back out the supply chain of each (publicly listed) firm appearing as contract winners in the DoD records. Keeping with our example, Figure 2, depicts the information on suppliers (and supplier of suppliers) of General Dynamics in 1990. Again, by merging this information with data on R&D expenditures and patents filed, allows us to study the impact on innovation of a final demand, market size increase, across the supply chain.

Our empirical results uncover evidence of sizeable cascading market size effects. For example, the elasticity of patenting and R&D with respect to the market size shocks is about half that of the elasticity for directly received defense procurement funds. This pattern is consistent across the outcomes of sales, patents, cite-weighted patents and R&D.

In terms of the identification strategy, we find that the OLS estimates for the direct effects

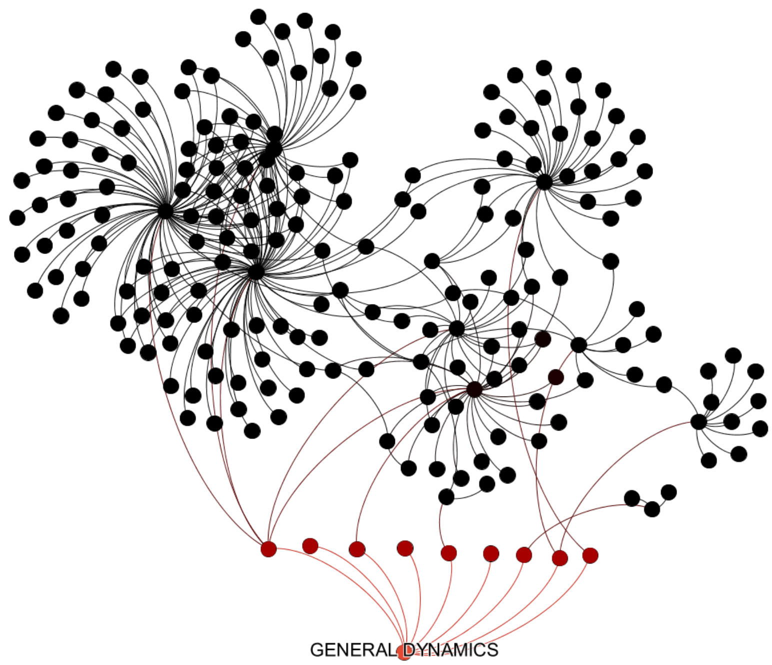


Figure 2. The Supply Chain of General Dynamics in 1990

Notes: The figure depicts the supply chain of General Dynamics in 1990 according to customer segment data in Compustat. In that fiscal year, nine publicly listed firms (in red, upstream of General Dynamics) named General Dynamics as a major customer, under Financial Accounting Standards Rule No.131. In turn, these suppliers were named by other publicly listed firms (in black, further upstream) as important customers themselves. *Source:* Compustat.

of defense procurement are biased downwards (that is, the IV estimates that use the firm-specific Bartik instrument are higher than the OLS). However, the magnitude of the OLS and IV estimates for the cascading effects are comparable. This is consistent with the hypothesis that endogeneity concerns arising from the targeted allocation of spending by the DoD are less of a concern as we move along the supply chain.

Finally, we calculate the in-sample magnitude of the cascading effect. After taking into account the elasticities and the size of the realised shocks, we find that the total cascading effect is approximately one-fifth the size of the direct effect of defense procurement spending on firms. This is a lower bound insofar as our supply-chain data does not measure lower value customer-supplier relationships.

Related Literature Our work is closely related to a series of recent works exploring the link between market size and the strength and direction of innovation activities. Acemoglu and Linn (2004) and Finkelstein (2006) are two seminal studies showing how market size effects - driven, respectively, by the ageing of the population or by policy-induced vaccine demand -

has had strong effects on innovation in the market for pharmaceuticals and vaccines, respectively.[1] Relative to this literature, we make two contributions. First, by exploiting the detailed information in DoD procurement records and linking it with firm-level innovation decisions, we are able to detect market size effects at the firm-level. Second, by exploiting supply chain information for the winners of DoD contracts, we are able to show that final demand market size fluctuations in turn translate into recursive market size effects working up the supply chain and induce innovation for firms upstreams of the final demand stage.

Our work is also closely related to a small literature looking at the role of government demand on innovation. Cozzi and Impullitti (2010) present a growth model where the technological composition of government spending matters for innovation. Specifically, they outline a 'demand-pull' channel where a shift towards spending on high-tech goods increases the rewards for innovation and ultimately has an effect on the relative demand for skilled workers. Slavtchev and Wierderhold(2016) present evidence in favor of this hypothesis by exploiting variation in federal procurement across US states. Specifically, they show that shifts towards procurement in high-tech industries induces additional R&D spending at the state level. Finally, Ruttan (2006) presents a detailed historical account that tracks the role of military funding in the development of crucial general purpose technologies such as jet passenger aviation, computing, nuclear energy and, most recently, the global positioning system (GPS) network. This historical literature suggests that the contribution of military spending to innovation could be significant but there is limited microeconomic evidence to support this at the level of individual firms. Relative to this literature, we present firm-level evidence of the impact of military spending on innovation and analyse how these market size effects cascade across the supply chain.

This paper is also related to the recent collection of papers, such as Acemoglu et al. (2012, 2016), Baqaee (2016), Barrot and Sauvagnant (2016), Carvalho (2014), Carvalho et al (2016) and Bigio and La'O (2016), that emphasizes the role of input-output linkages as a mechanism for the amplification of micro-level shocks, affecting only a small subset of firms, sectors or regions. As in this literature, we show that input-linkages serve as a conduit for the propagation of shocks. Differently from this literature, we focus on demand-led cascades working up the supply chain, from customers to their suppliers (rather than the more usual case of supply shocks cascading down, from suppliers to customers). Furthermore, we differ in the outcomes of interest. Thus our focus is on innovation and R&D outcomes following final demand market size increases rather than output comovement following productivity shocks.

Finally, our work is also related to a large literature on technology spillovers. For example, the work by Bloom et al (2013) emphasizes the empirical relevance of knowledge spillovers (alongside product market rivalry) across firms. As in this literature, our work focuses on the transmission of R&D and innovation across firms. Differently from this literature, we focus

[1] See also the earlier studies on demand-side influences in energy sector innovation by Newell et al (1999) and Popp (2002).

on pecuniary spillovers from cascading market size effects via input-linkages.

Outline The rest of the paper is organized as follows. Section 2 introduces our theoretical framework highlighting the role of cascading market size effects in the simplest possible setting. Section 3 gives some background on defense procurement in the US. In Section 4, we review the three main sources of data used in the paper: DoD procurement records, firm-level outcomes from Compustat and firm-level patent information from the NBER database. Section 5 details our empirical strategey and presents the key results. Section 6 concludes. The proofs are provided in the Appendix.

2 Analytical Framework

We consider the empirical implications of a simple model of R&D with two vertically related layers of production, where a downstream final goods producer sources inputs from two upstream intermediate input supplier. This provides the simplest possible setting to demonstrate the presence of recursive market size effects and their impact on innovation across the supply chain.

The upstream firms produce a single homogeneous input that they sell to the downstream firm at a price P_u. The downstream firm is a final goods producer selling its single homogeneous product to final consumers. The downstream firm use one unit of the input to produce one unit of output. We assume for now that the downstream firm purchases an equal amount of the input from each upstream firm. The downstream firm faces a linear inverse demand function:

$$P_d(X) = a - X,$$

where $a > 0$ and X is the final goods output.

Both upstream and downstream firms may invest in R&D. Doing so reduces their marginal cost of production. The production cost of the downstream firm is

$$c_d = c(E_d) + P_u,$$

where E_d is R&D expenditures by the downstream firm, and likewise, the production cost of upstream firm i is

$$c_{ui} = c(E_{ui}).$$

Note that we are assuming that the upstream firms do not need intermediate inputs in order to produce; this assumption can be easily relaxed without changing any of our predictions below. Further, we will assume the following constraints on the function $c(\cdot)$:

Assumption 1. $c(\cdot) > 0$ is a continuous and twice differentiable function such that $c'(\cdot) < 0$, $c''(\cdot) > 0$, and $c(0)$ is finite.

That is to say, costs are decreasing and convex in R&D expenditure, and finite in the absence of R&D.

The model has three stages. In the first stage, firms simultaneously choose R&D expenditures. In the second stage, the upstream firms simultaneously set output to maximize profit. In the final stage, the downstream firm chooses output to maximize profits. We solve for a sub-game perfect Nash equilibrium by backward induction.

Thus, in the last stage the final goods firm will choose output to maximise profits such that:

$$x = \frac{a - c(E_d) - P_u}{2}.$$

Therefore, upstream firms face an inverse demand function:

$$P_u(Y) = a - c(E_d) - 2Y.$$

where Y is the demand for intermediate inputs by the downstream firm. We can then solve for equilibrium outputs as a function of R&D expenditures:

$$y_i^* = \frac{a - c(E_d) - 2c(E_{ui}) + c(E_{uj})}{6},$$

$$x^* = \frac{a - c(E_d) - c(E_{ui}) - c(E_{uj})}{6}.$$

where y_i^* gives the equilibrium output of upstream firm i.

We can now turn to the first stage and find the equilibrium levels of R&D expenditure. Using the above equilibrium output levels, choosing R&D expenditures to maximize profits and imposing symmetry for the upstream firms gives:

$$(a - c(E_d) - 2c(E_u))c'(E_d) = -18, \tag{1}$$

$$(a - c(E_d) - c(E_u))c'(E_u) = -\frac{9}{2}, \tag{2}$$

where the former is the condition for downstream firm and the latter holds for upstream firms. Our equilibrium is then given by the intersection of these two conditions. In the Appendix, we show that for a sufficiently large a, there exists a unique interior solution to this simple game.

We are now interested in understanding how profits, output and R&D levels respond to an increase in the final goods market size. In our simple framework, this is equivalent to understanding the comparative statics of the model with respect to an increase in a, in the inverse demand function in the final goods market. The following Proposition summarizes our results.

Proposition 1. *Under Assumption 1, for a large enough, increasing the market size for the downstream final good $(a \uparrow)$ leads to (i) larger profits for upstream and downstream firms,*

$$\frac{\partial \pi_d}{\partial a} > 0 \;\&\; \frac{\partial \pi_u}{\partial a} > 0$$

(ii) larger output for upstream and downstream firms,

$$\frac{\partial x}{\partial a} > 0 \;\&\; \frac{\partial y}{\partial a} > 0$$

and (iii) higher levels of R&D expenditures for upstream and downstream firms,

$$\frac{\partial E_u}{\partial a} > 0 \;\&\; \frac{\partial E_d}{\partial a} > 0$$

We present the proof of the above proposition in the Appendix. Intuitively, there are market size effects on innovation operating across the supply chain: increasing the extent of the market makes it worthwhile for both the final goods supplier and intermediate goods firms to engage in cost-reducing innovation. In particular, note that the downstream firm exhibits a direct market size effect which is further enhanced by a cost reduction effect on its intermediate inputs (given upstream innovation). At the same time, following an expansion of the final goods market, the upstream suppliers a (derived) demand increase. That is, increasing the size of the final demand goods' market leads to recursive market size effects up the supply chain.

3 Defense Procurement

In this section we discuss the main features of US defense procurement policy relevant to this study. An important background feature to DoD policy is the way that procurement spending decisions are taken. Specifically, the DoD purchases its major goods and services on both a competitive and non-competitive basis following a 'life-cycle' model. For example, when the DoD commissions a new weapons system it establishes a 'technical design competition' and solicits detailed, scientific proposals from potential contractors. Firms contest this stage vigorously because winning a design contest assures them of receiving non-competitive follow-on contracts. These follow-on contracts relate to supply and maintenance – since the firm designed the weapon system it has monopoly power over its ongoing provision. The DoD's power in this situation depends on its ability to substitute across weapons system which according to a study by Lichtenberg (1990) is limited . The uncertainty inherent in high-tech defense projects (Peck and Scherer 1962) also means that costs for the DoD often increase after the competitive stage, enhancing the financial position of the locked-in contractor.

Practically, the DoD supports the design competition process by providing on ongoing R&D subsidy for firms so that they are primed to submit detailed technical bids. The effects of the DoD's overall policies are therefore felt by firms both on the demand-side (through procurement policy) and the supply-side (via the R&D subsidy). O Procurement contracts such as those offered by the DoD are therefore best framed as demand shifters affecting the marginal rate of return for investments . As discussed, contracts for R&D services are frequently coupled with valuable, non-competitive follow-on contracts for the final goods designed as part of the research process. The large demand component therefore has the effect of moving the firm MRR schedule outwards. Furthermore, this is not a secular increase in demand but rather one that applies for military-related innovation investments. Following the introductory discussion, the increased emphasis on military-related investments could then have a positive or negative effect on the subsequent innovation outputs of firms (chiefly measured in this paper by patents).

This type of shift in the MRR contrasts with the effects of a direct R&D grant or subsidy. Such policies increase the effective level of internal funds and shift the MCC schedule to the right. It should be noted that there is a clear distinction in DoD policy between procurement and subsidy-based R&D funds. The DoD administers a subsidy policy known as the Independent Research and Development (IR&D) program. This program reimburses firms for the overhead costs incurred as part of non-contract work that is related to military R&D priorities broadly defined. The work is independent in the sense that the research projects involved are selected and initiated by the private company itself. The main objective of the program is to underwrite the efforts of firms in participating in technical design competitions for new projects as outlined in the previous section. The role of the IR&D program was studied in detail by Lichtenberg (1989, 1990).

Given this overall background, this paper mainly treats procurement spending as working through the demand–side of the firm innovation investment decision. While some shifts in the MCC could still be induced by changes in procurement spending policy the majority of procurement effects are likely to fall on the demand-side. However, the presence of the IR&D program complicates the analysis. This program operates in parallel to procurement spending and will have the effect of pushing the MCC outwards.

Systematic data on the IR&D subsidy is not as readily available as the information on procurement but some conclusions about its influence can be drawn. Firstly, the level of the IR&D subsidy is determined by a formula that depends in part on lagged level of procurement spending. As such, the IR&D subsidy will be correlated with firm procurement receipts, albeit with a delay . Secondly, while the IR&D subsidy is valuable to firms it is still small compared to the total value of procurement. For example, Lichtenberg (1990) calculates that allowable costs under the IR&D policy were worth \$3.5billion in 1986 for all contractors which represents only 2.5% of the total procurement budget. The ultimate implication of this correlation between the two policies (that is, the IR&D subsidy and procurement spending) is that the reduced form estimates I present below will be picking up some degree of shift in the MCC along with the bigger effects of procurement on the MRR.

4 Data

Three main datasets are used to build the long-run firm panel used in this paper: historical military procurement data from the National Archives and Records Administration (NARA); US Patent and Trademark Office (USPTO) information on patents (as compiled by Hall, Jaffe and Trajtenberg (2002) as part of their NBER project); and company accounts data along with supply chain data sourced from COMPUSTAT. The details of each dataset are discussed in turn.

4.1 Department of Defense Procurement Contracts

The NARA historical files on military procurement contain all prime military contracts awarded by the Department of Defense (DoD) since the 1966 Fiscal Year (FY) and until FY 2003. After 2003, the DoD changed its procurement reporting format. It began to report its procurement information as part of the highly complicated Federal Procurement Data System (FPDS).

The file for each FY contains records on approximately 250,000 different contracts awarded by all DoD sub-agencies for the purchase of goods and services. The records are drawn from a standardized departmental form known as the DD 350 or more eloquently as the "Individual Contracting Action Report". The minimum reporting threshold for purchases is $10,000 for FY1966 – FY1983 and $25,000 for FY1984 onwards.

The data are exhaustive and summarize many details of each contract, such as: the names and unique identifiers of the awardees; contracting office within the DoD; types of contracts (e.g. competitive versus non-competitive); dates of action; estimated completion date; geographic location of the contractor (city, county and state); weapon system code; and importantly a 4-digit product code (known as the Federal Supply Code (FSC)). While there is some addition and deletion of products the FSC classification is consistently defined from 1966, making it feasible to define a 155 product panel across the 1966-2003 period. The NARA data are probably the most detailed historical data on government procurement available anywhere and were only released in this form in the late 2000s. As a result, research using these military procurement files is still very limited. Some examples of work that uses defense procurement data of this type includes Hines and Guthrie (2011) and Nakamura and Steinsson (2011), along with the Frank Lichtenberg's program of work in the 1980s and early 1990s (summarized in Lichtenberg 1995).

4.2 Firm-Level Outcomes and Supply Chain Linkages Data

The Compustat database provides accounts information on publicly listed firms, with annual information available from 1950 onwards. We extracted the raw data for all firms from 1966 onwards. In cleaning the sample, all accounting and procurement variables were winsorized at the 1st and 99th percentiles. The final sample reported in the regressions from Table 2 onwards drops all firms with fewer than four years of consecutive data. Furthermore, note that the sample used from Table 2 also conditions on the existence of a 10-year lag for procurement receipts and therefore begins in 1976. This is because the proposed exogenous shocks term is based on 10-year lagged product shares.

We source two types of data from Compustat. First, we use standard balance sheet information as either firm-level outcomes or controls. Thus, firm sales (mnemonic SALE) is used as the output measure; the net stock of property, plant and equipment (PPENT) is used for the book value of capital, and the labour input is represented by employees (EMP). The R&D capital stock is defined following the perpetual inventory method (PIM) using a 15% depreciation rate as where represents the flow of R&D expenditures (mnemonic XRD). Note that this is also the approach taken for the calculation of patent stocks using the USPTO data. The return on assets is defined as Net Income (NI) over Current Assets (ACT). The return on sales from data on Sales, Cost of Goods Sold (COGS) and Selling and Administrative Costs (XSGA).

Secondly, we utilise COMPUSTAT's information on supply chain linkages among publicly listed firms. This is possible because, in accordance with the Financial Accounting Standards Rule No.131, publicly listed firms are required to disclose the identity of their major customers. A major customer is defined as any firm responsible for more than 10% of the seller's revenues, although firms occasionally report the identity of customers below that threshold. This firm-level network data can then be linked to the balance sheet information in Compustat, allowing us to associate information on firms' customers and suppliers with other firm-level observables.[2] The raw data is reported annually and covers the period from 1977 to 2008 for a total of 43,506 firm-to-firm links.

4.3 Patents Data

The final key dataset for the project is the NBER US Patents Database (Hall et al. 2002). These data were produced as part of an ongoing NBER project that processes raw USPTO patent data and matches patent assignees against the full historical set of stock-market listed firms. The data were first produced in 1999 with an update in 2006 and ongoing work to deepen the dataset.

The NBER Patents data provides the frame for the name matching exercise that we conduct across the three datasets. That is, we used the list of the assignees from the NBER database as the main source of names to be matched to the NARA procurement database. The string-based name-matching is implemented using the usual procedures outlined in work such as Hall et al (2002). The presence of Dun and Bradstreet (DNB) business numbers allows us to consolidate establishments in the procurement data to the HQ level before

[2] **?** were the first to explore firm linkages from this data source to examine return predictability across linked firms. **?** also use these data to show that firm level volatility depends on the structure of buyer-supplier linkages. Finally, **?** use the same data source to develop a model of the buyer-supplier networks in the U.S. economy. We are grateful to the latter set of authors for sharing their data with us.

matching. For completeness, we match COMPUSTAT company names directly to the procurement database to capture cases where firms receive defense contracts but do not necessarily patent. Finally, we also manually match assignees and contractors in cases where high-value contracts cannot be matched using the automatic method. Final match rates are high in weighted dollar value terms. Approximately 78% of contracts by weighted value are matched to either the NBER Patents Database or COMPUSTAT. This rises to around 94% for contracts classed under R&D product codes.

5 Empirics

5.1 Empirical Strategy

Our empirical strategy is based on tracing the propagation of defense spending shocks from their initial receipt by a sub-group of major defense contractors through to the suppliers of these contractors, and then to the suppliers of these suppliers further down the transaction chain. As part of our identification strategy, we also explicitly model how shifts in firm-specific market size at the level of the top contractors affects firms further down the supply chain.

Direct Effects and DoD Market Size Instrument.

The framework that we build first concentrates on tracing out the direct impacts of receiving defense contracts on the initial contractors. We will denote these firms as 'customer firms' k since they serve as the customers of the supplier firms that will be the main focus of our analysis. Modelling of the direct effects of defense contracts on the set of customer firms k is framed simply as:

$$y_{kt} = \alpha_k + \delta d_{kt} + X'_{kt}\pi + \gamma_t + \zeta_{kt} \tag{3}$$

where y_{kt} generically denotes an outcome such as firm sales, R&D, or patents. The variable d_{kt} measures the total value of defense contracts received by firm k in period t, γ_t represents time effects, X_{kt} is a vector of controls, α_k is the firm fixed effect and ζ_{kt} is the error term. The functional forms used in implementation will depend on the variables involved but the major modelling issue is the potential endogeniety of the d_{kt} variable, which cannot be ruled out even after controlling for constant firm unobservables as part of α_k.

To be clear about the main sources of this endogeniety, it is logical that the DoD will award contracts to firms that are already highly innovative – indeed the competitive structure of the procurement process is designed to do this (subject to price considerations). It is also plausible that the DoD may target areas of growing technological opportunity as part of its objective to build the best military equipment possible. To deal with this endogeniety issue we define a Bartik-style IV strategy that leverages the detailed product-level information that is available as part of the Federal Supply Code (FSC) system. Specifically, this approach is based on taking the lagged product specialization of a firm and then calculating the current demand for the firm's product portfolio based on DoD procurement spending.

The premise of this approach is that firms have a pre-existing specialization in particular types of goods that are purchased by the DoD. As the DoD varies its spending year by year then the size of the potential 'defense market' for the firm changes. Furthermore, if the firm's shares across product groups are defined with a sufficient lag we can limit the influence of situations where firms endogenously enter into new product categories where the DoD is increasing spending. The lagged pattern of specialization is therefore designed to capture the firm's core products for sale to the DoD.

We can express this by first defining the historical product shares (here using a 5-year lag) for a firm:

$$\phi_{kl,t-5} = \frac{d_{kl,t-5}}{\sum_{l=1}^{L} d_{kl,t-5}} \tag{4}$$

where the DoD product codes are denoted by l and each customer k has a portfolio of product codes ($l = 1, ..., L$) for purchase by the DoD. At the level of the DoD we can then define aggregate annual spending according to 2-digit product code as D_{lt}. Hence the level of total product demand for firm k in the current period can be calculated as follows:

$$m_{kt} = \sum_{l=1}^{L} \phi_{kl,t-5} D_{lt} \tag{5}$$

This expression therefore measures how the DoD's spending patterns affect firm k based on a predetermined, historical specialization. A key assumption here is that no individual firm can affect the level of demand in product group l (for example, via political lobbying). The efficacy of this assumption can be tested by studying the pattern of spending at the product group level and relating it to group characteristics such as concentration ratios, market power or political clout.

Modelling Cascade Effects

The transmission of the the customer k level spending shocks through the supply chain is then the next (and primary) focus of our analysis. The direct shocks at the level of the top defense contractors will flow through to the supplier level based on the input shares for each customer-supplier relationship. Simply put, the initial spending shocks will flow through most heavily to the customer firm's most important suppliers.

Define θ_{ik} as the share of inputs that customer k purchases from supplier i. The amount of defense dollars that will flow through from customer k to a particular supplier i is calculated simply as: $c_{ikt} = \theta_{ik} d_{kt}^{L}$. The supplier receives these amounts of derived demand across multiple purchasers of its goods. Hence we aggregate across the K customers of each supplier i

to get the full cascading shock:

$$c_{it}^K = \sum_{k=1}^{K} c_{ikt} \tag{6}$$

This term can be defined with respect to multiple levels of the supply chain. For example, the input share weighted demand shock c_{ikt} will be further transmitted to the supplier of the supplier. At each stage there will be an attenuation of the original d_{kt} shock according to the relevant θ_{ik} input share that applies at that point. These different levels of cascading shock can be accumulated across stages to construct a single aggregate measure of c_{it}^K.

Our overall analysis is then based on the sample of all suppliers i where we relate an outcome y_{it} to the cascading shock c_{it}^K and other covariates. We can then frame a generic outcome equation for these supplier firms as:

$$y_{it} = \alpha_i + \beta c_{it}^K + X_{it}'\lambda + \tau_t + \epsilon_{it} \tag{7}$$

where X represents available controls and τ_t and ϵ_{it} are the time effects and error term respectively. We have kept the X_{it} very general in this exposition but some key controls that we will include are firstly d_{it}, which measures the direct receipt of defense contract sales from the DoD, and secondly g_{it}, which we frame as all other sources of non-pecuniary spillovers (for example, knowledge spillovers arising from industry R&D or patent stocks).

The market size shock m_{kt} term can also be aggregated as it passes through different stages of the supply chain. We can write this as $z_{it}^K = \sum_{k=1}^{K} \theta_{ik} m_{ikt}$ such that we aggregate all of the customer level m_{kt} market size shocks for supplier i across all of its' k customers per period t. Again, the input shares will mediate how affected specific suppliers are by the original, customer-level m_{kt} shock.

The z_{it}^K variable can then be used to instrument the derived demand c_{it}^K. The key strength if this IV strategy is that the market size shock that is affecting the suppliers is at least one step removed from the original decision by the DoD to allocate spending. This obviously limits the scope for biases to emerge directly as the result any (implicit or explicit) decision rules by the DoD that target innovative opportunities.

5.2 Results

In discussing the results we first review some descriptive statistics on both our sample of firms and then the nature of the product-level variation in DoD procurement spending. We then present the results for the models of direct and cascading effects of spending on firms outlined above.

Descriptive Statistics

Table 1 presents the basic descriptive statistics for the main samples of firms that we work with. These firms can be divided into a 'customer' and 'supplier' group based on the firms presence in the Compustat market segment file. For example, over the 1976-2003 period that we study there are 2,192 firms who are recorded as customers of another firm and then 5,725 recorded as supplying goods and services. It is evident that the customer firms are bigger across a range of size measures, with about 33% higher average sales at the median. This reflects a supply chain structure in the data where big firms purchase inputs from smaller supplier firms.

A central part of our empirical strategy is the product-level variation in DoD procurement spending. In Figure 3, we first show the total annual value of DoD procurement contracts from 1966-2003. A spike at the end of the Vietnam war is followed by a retrenchment of spending before the large build-up during the Reagan administration. The last cycle of spending over this period then reflects the post-Cold War cutbacks under Clinton and the resurgence of spending in the wake of 9/11.

However, our key point here is that underpinning these spending cycles are some sharp compositional shifts, particularly from the late 1980s onwards. Figure 4(a) illustrates the breakdown of the top 10 two-digit products within total DoD procurement, showing a dominance of R&D along with capital-intensive weapons or equipment categories such as aircraft, ships, engines and missiles. The following Figure 4(b) then shows the evolution of this top 10 group within total spending, charting a fall in their share of spending from nearly 60% in the 1970s and 1980s to around 40% by the end of the period covered. This reflects a diversification of spending by the DoD as it shifted away from the development of capital-intensive weapon systems.

This variation in the product composition of spending is the basis of our firm-specific measure of market size. A critical issue for this measure is the potential relationship between DoD spending patterns and form characteristics. Specifically, it is important to gauge the potential for reverse causality between the market (or indeed political) power of firms and the DoD's spending decisions.

In Table 2 we therefore analyse the DoD's procurement spending at the 2-digit product level and relate this to lagged concentration patterns within these product categories. Our main Herfindahl measure is based on firm market shares with respect to total DoD spending for the product. The concern would be that DoD spending levels are more persistent in 2-digit categories with higher levels of firm concentration, possibly as a result of political lobbying by firms or general institutional inertia. The results indicate that, if anything, DoD spending is being withdrawn from the 2-digit categories with higher levels of concentration, with an insigificant negative coefficient on our lagged Herfindahl measure.

Direct Effects

In Table 3 we analyse the association between firm defense procurement receipts and outcomes for the top contractors who act as the 'customers' to the supply chain network that we study later. The sample used conditions on all of the 'innovating' firms in Compustat, that is, only those firms who have a filing a patent at some point in time. This leaves us with a sample of 1,238 firms and the main outcome measure we consider are sales, patent counts, cites and R&D expenditures. For this analysis, we use the ‘log 1 plus’ normalization when the patent count equals zero for a firm-year cell and we also do this for our defense sales measures. Hence, the estimates shown reflect movements along both the intensive and extensive margins of receiving money from the DoD.

The results show a strong positive association between defense procurement sales and outcomes across all measures. All regressions are estimated on a within-firm basis using firm fixed effects. The OLS estimates indicate that a 10% increase in defense sales is associated with a 0.39% increase in patenting (ie: approximately four-tenths of one 1%). A similar effect is evident for R&D (a 0.32% increase) and there is an even stronger association for the cite-weighted patent count measure (0.7%).

The IV results (reported in panels A and B of Table 2) employ the 5-year lagged, firm-specific market size instrument as a direct shifter for current defense sales. The first stage is clearly very strong and the market size measure explains an important fraction of firm receipts - a 10% increase in market size is associated with a 2.6% increase in defense procurement sales received by the firm. The subsequent IV estimates are also up to two times larger than the OLS estimates, indicating that the contemporaneous measures of defense procurement sales do not fully reflect the innovation response of firms to the structural shifts in market size that we are measuring.

Cascade Effects

The initial analysis of the indirect or ‘cascade’ effects of defense spending shocks is reported in Table 4. Again, this uses the set of innovating firms resulting in a sample of 2,584 suppliers. Our main specification uses firm fixed effects and includes any directly received defense procurement receipts as a control variable. The estimates of direct effects here are analogous in size to those of the previous customer firm sample.

The variable for the cascading amount of defense sales measures all of the indirect sales shocks received by the firm across three levels of the production network. That is, the cascade measures the initial customer to supplier shock plus the next round of supplier-to-supplier transactions and a further round after that. The estimates show that the coefficients associated with these cascade effects are around half the size of the direct effects across all the outcomes.

We control for SIC4-year effects in panel B. This plays the useful role of controlling for any sources of non-pecuniary spillovers (for example, knowledge spillovers emanating from industry R&D stocks) that might be correlated with our cascade measures. The coefficient values on the cascade variable are largely unaffected by this, bearing out the firm-to-firm rather than industry level nature of our measure.

The firm-specific market size is then used to instrument cascading sales in Table 5. The first stage coefficient is large (approximately 0.60),indicating that the cascading sales move closely with the market size instrument. However, it is noticeable that the 2SLS estimates in this cascading case are comparable in magnitude to the initial OLS estimates. This is consistent with the hypothesis that endogeneity in the allocation of defense contracts is less of a concern as we move further along the supply chain away from the direct spending choice made by the DoD.

Another important dimension of the results is the within sample magnitudes. That is, what is the relative importance of the direct and cascading effects of DoD contracts when we take the size of the realised shocks into account? To calculate this we multiply the coefficients for the direct and cascading effects by the median values of the variables to obtain the predicted in-sample effect. We then re-weight the predicted cascade effect by relative number of non-zero values. This is because the cascading shocks are approximately 20% sparser than the direct defense spending shocks. In total, we then estimate that the in-sample cascading effect is around 21% of the size of the direct effect. Hence the cascading effect boosts the direct effects of defense procurement spending on aggregate innovation by one-fifth. This is a lower bound insofar that our data does not pick up the smaller customer-supplier relationships (ie: those below the 10% threshold set by the Financial Accounting Standards Rule No.131).

6 Conclusion

In this paper, we have provided a study of market size effects on innovation based on the propagation of a large-scale demand shock. The data we have assembled on defense contracts, supply chain linkages and innovation measures allows us to track how the aggregate spending decisions made by the DoD are transmitted through the microeconomic structure of firms in the listed sector of the economy. This means that we are able to measure both a traditional market size effect, whereby enlarging the extent of the market, renders final goods firms larger, more profitable and more innovative, as well as cascading market size effect along the supply chain.

Our modelling is facilitated by the rich composition of DoD spending that lets us create firm-specific measures of defense sales opportunities across firms. The results indicate a significant response of firms to the direct receipt of defense procurement sales including a strong response to immediate DoD market size across firms and products. This effect is complemented by the transmission of the DoD market size shocks along the supply chain. The elasticity of patenting and R&D with respect to the cascading shocks is around half that of the direct elasticity according to our empirical models. The overall in-sample magnitude for the cascading effect is calculated to be approximately one-fifth of the direct effect and this is likely to be a lower bound. Crucially, the scale and sectoral breadth of defense spending in the US economy means that our setting has high external validity and is therefore able to establish an important macroeconomic role for market size effects in stimulating growth.

A Technical Appendix

This is a proof Appendix to Section 2. We start by showing that for a sufficiently large market size, there exists a unique interior solution to the model laid out in Section 2. We then prove formally the main comparative statics result.

Proposition 2. *Under Assumption 1, for sufficiently large market size, a, there exists a unique interior solution.*

Proof: From the first order conditions given in the main text, we have that

$$F_d(a, E_d, E_u) = (a - c(E_d) - 2c(E_u))c'(E_d) + 18 = 0.$$

By the Implicit Function Theorem, we then have that

$$\frac{dE_u}{dE_d} = \frac{-\frac{\delta F_d}{\delta E_d}}{\frac{\delta F_d}{\delta E_u}} = \frac{c''(E_d)(a - c(E_d) - 2c(E_u)) - c'(E_d)^2}{2c'(E_d)c'(E_u)} \tag{8}$$

And likewise we have

$$F_u(a, E_d, E_u) = (a - c(E_d) - c(E_u))c'(E_u) + \frac{9}{2} = 0.$$

So differentiating implicitly

$$\frac{dE_u}{dE_d} = \frac{-\frac{\delta F_u}{\delta E_d}}{\frac{\delta F_u}{\delta E_u}} = \frac{c'(E_d)c'(E_u)}{c''(E_u)(a - c(E_d) - c(E_u)) - c'(E_u)^2} \tag{9}$$

Under Assumption 1, $c(\cdot) > 0$, $c'(\cdot) < 0$, $c''(\cdot) > 0$, and $c(0)$ is finite. Therefore, for sufficiently large a, we have that for the locus described by (1)

$$\frac{dE_u}{dE_d} > 1$$

and for the locus described by (2)

$$0 < \frac{dE_u}{dE_d} < 1.$$

Furthermore, since $c(0)$ is finite, there exists a point $(\bar{E}_d, 0)$, such that

$$F_d(a, \bar{E}_d, 0) = 0,$$

for any a. Similarly, we must have a point $(0, \bar{E}_u)$, such that

$$F_u(a, 0, \bar{E}_u) = 0,$$

for any a. Therefore, for sufficiently large a we must have a unique intersection of the two loci.

Proposition 3. *Under Assumption 1, for a large enough, increasing the market size for the downstream final good $(a \uparrow)$ leads to (i) larger profits for upstream and downstream firms,*

$$\frac{\partial \pi_d}{\partial a} > 0 \,\&\, \frac{\partial \pi_u}{\partial a} > 0$$

(ii) larger output for upstream and downstream firms,

$$\frac{\partial x}{\partial a} > 0 \,\&\, \frac{\partial y}{\partial a} > 0$$

and (iii) higher levels of R&D expenditures for upstream and downstream firms,

$$\frac{\partial E_u}{\partial a} > 0 \,\&\, \frac{\partial E_d}{\partial a} > 0$$

Proof: By Proposition 2 there exists some neighbourhood for which we have a unique solution for (E_d, E_u) in terms of a. Therefore, differentiating (7) and (8) implicitly with respect to a, we have that

$$(1 - c'(E_d)\frac{\delta E_d}{\delta a} - 2c'(E_u)\frac{\delta E_u}{\delta a})c'(E_d) + (a - c(E_d) - 2c(E_u))c''(E_d)\frac{\delta E_d}{\delta a} = 0 \tag{10}$$

$$(1 - c'(E_d)\frac{\delta E_d}{\delta a} - c'(E_u)\frac{\delta E_u}{\delta a})c'(E_u) + (a - c(E_d) - c(E_u))c''(E_u)\frac{\delta E_u}{\delta a} = 0 \tag{11}$$

We can rewrite this system as

$$\begin{pmatrix} c'(E_d)^2 - (a - c(E_d) - 2c(E_u))c''(E_d) & 2c'(E_u)c'(E_d) \\ c'(E_u)c'(E_d) & c'(E_u)^2 - (a - c(E_d) - c(E_u))c''(E_u) \end{pmatrix} \begin{pmatrix} \frac{\delta E_d}{\delta a} \\ \frac{\delta E_u}{\delta a} \end{pmatrix} = \begin{pmatrix} c'(E_d) \\ c'(E_u) \end{pmatrix}$$

Therefore,

$$\begin{pmatrix} c'(E_d)^2 - (a - c(E_d) - 2c(E_u))c''(E_d) & 2c'(E_u)c'(E_d) \\ c'(E_u)c'(E_d) & c'(E_u)^2 - (a - c(E_d) - c(E_u))c''(E_u) \end{pmatrix}^{-1} \begin{pmatrix} c'(E_d) \\ c'(E_u) \end{pmatrix} = \begin{pmatrix} \frac{\delta E_d}{\delta a} \\ \frac{\delta E_u}{\delta a} \end{pmatrix}$$

$$= \frac{1}{DET} \begin{pmatrix} c'(E_u)^2 - (a - c(E_d) - c(E_u))c''(E_u) & -2c'(E_u)c'(E_d) \\ -c'(E_u)c'(E_d) & c'(E_d)^2 - (a - c(E_d) - 2c(E_u))c''(E_d) \end{pmatrix} \begin{pmatrix} c'(E_d) \\ c'(E_u) \end{pmatrix}$$

where

$$DET = \left(c'(E_d)^2 - (a - c(E_d) - 2c(E_u))c''(E_d)\right)\left(c'(E_u)^2 - (a - c(E_d) - c(E_u))c''(E_u)\right) - 2\left(c'(E_u)c'(E_d)\right)^2$$

Under Assumption 1, $c(\cdot) > 0$, $c'(\cdot) < 0$ and $c''(\cdot) > 0$. Therefore, by inspection, we have that for sufficiently large a, $\frac{\delta E_d}{\delta a} > 0$ and $\frac{\delta E_u}{\delta a} > 0$. It follows that

$$\frac{dx_i}{da} > 0 \quad , \quad \frac{dy_i}{da} > 0,$$

$$\frac{d\Pi_d}{da} > 0 \quad \text{, and} \quad \frac{d\Pi_u}{da} > 0.$$

That is to say, profits and outputs of the upstream and downstream firms both increase with a.

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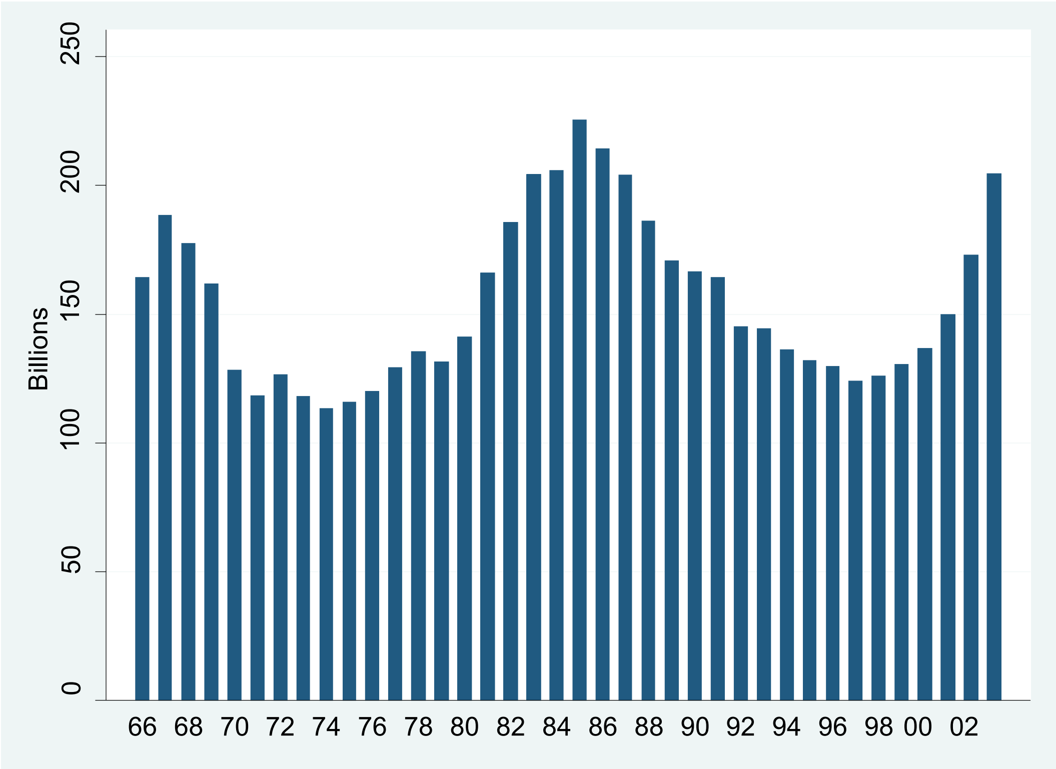
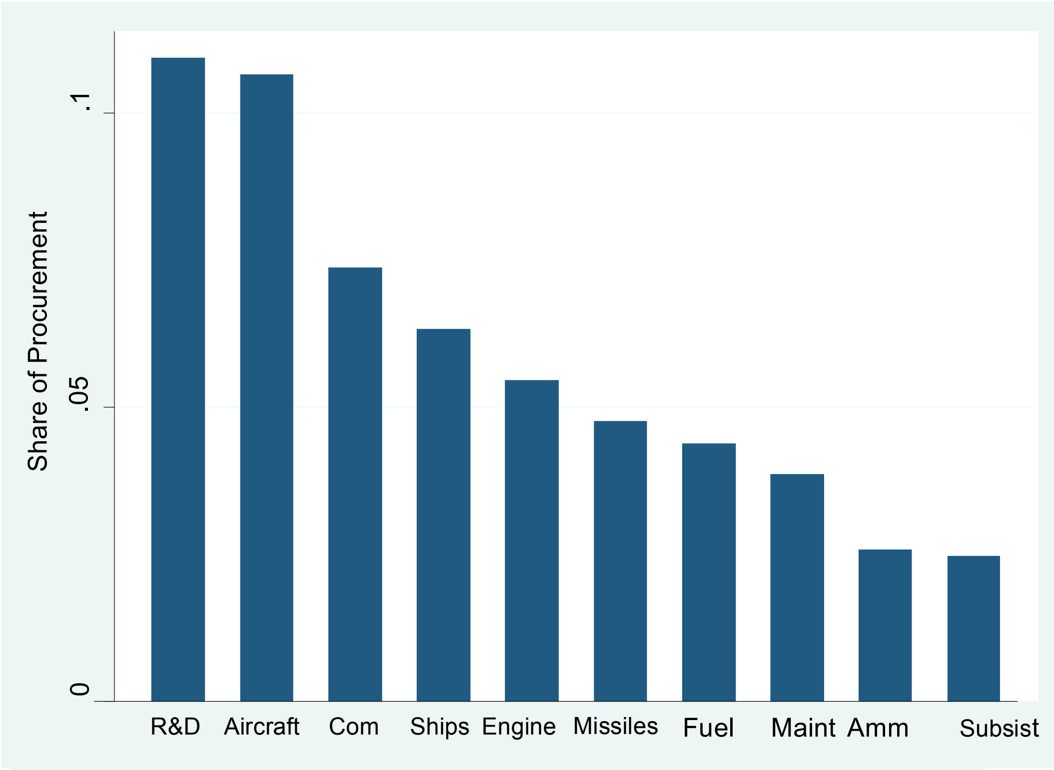
Figure 3: Total Defense Procurement Expenditure, FY1966 – FY2003.



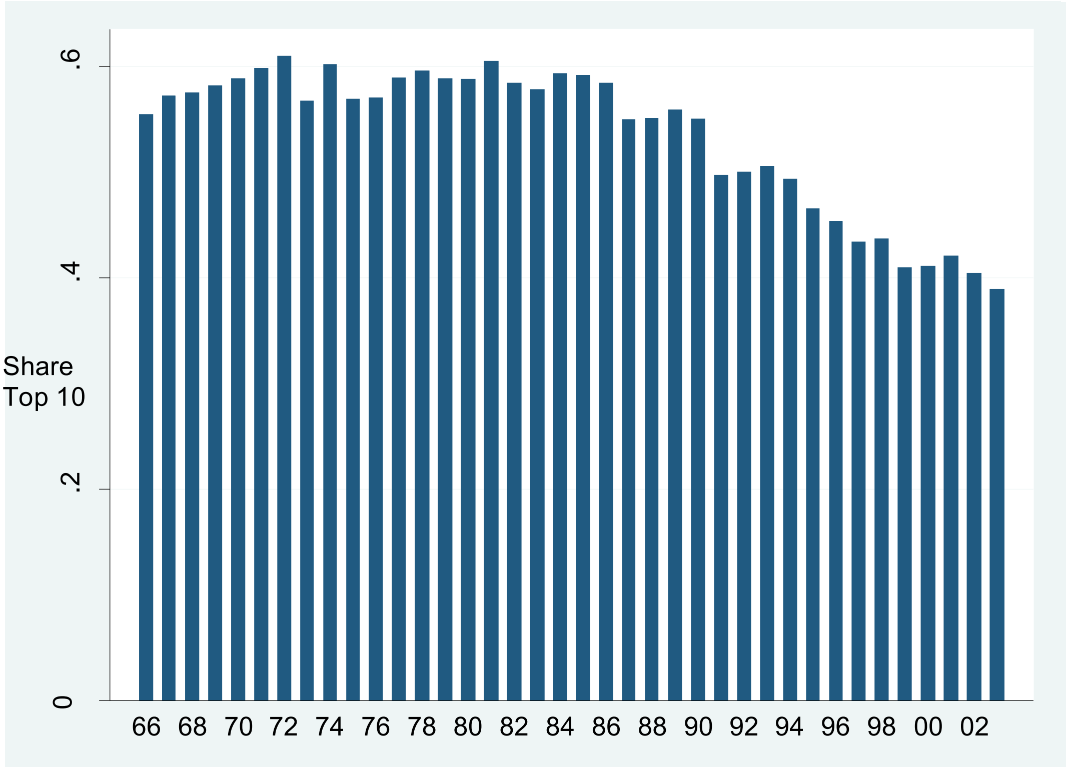
Notes: Reports total value of all prime military procurement contracts. Calculated from National Archives and Records Administration (NARA) Historical Files on military procurement. Deflated by the GNP deflator (base year 2003).

Figure 4a: Procurement Spending Shares, Top 10 2-digit Products.



Notes: These top 10 products are: R&D (for Equipment); Aircraft & Airframe Structural Components; Communications, Detection and Coherent Radiation equipment; Ships and Small Craft; Engines, Turbines and Components; Guided Missiles; Fuel and Lubricants; Ammunition & Explosives; Maintenance and Repair; and Subsistence. Note that the R&D (for Equipment) category includes R&D on Aircraft, Missiles, Ships, Tanks, Weapons and Electronics. Source is National Archives and Records Administration (NARA) Historical Files on military procurement.

Figure 4b: Share of Top 10 Products in Defense Procurement, FY1966 – FY2003.



Notes: This figure shows the share of the 'Top 10' 2-digit products by dollar value in total procurement spending. These top 10 products are: Aircraft & Airframe Structural Components; Ships and Small Craft; Engines, Turbines and Components; Communications, Detection and Coherent Radiation; Aircraft R&D; Ammunition & Explosives; Guided Missiles; Subsistence; Fuel and Lubricants; and Maintenance and Repair. Source is National Archives and Records Administration (NARA) Historical Files on military procurement.

Table 1: Characteristics of Customer and Supplier Samples, 1976-2003.

	(1) Customer Panel	(2) Supplier Panel
Patent Count	22.8	5.0
	(121.6)	(47.7)
Citation Count	195.3	41.7
	(1099.2)	(413.3)
Employment (in 1000s)	22.4	4.6
	(55.7)	(16.1)
Employment (median)	5.5	0.5
	-	-
Sales (in $1000s)	5825.7	979.1
	(1152.0)	(3640.1)
Sales (median)	1282.4	930.4
	-	-
(R&D/Sales)	0.056	0.102
	(0.097)	(0.156)
(Defense Sales / Sales)	0.020	0.015
	(0.084)	(0.070)
Number of Firms	2,192	5,725

Notes: Standard deviations in parentheses where applicable. This tables shows the characteristics of the customer and supplier sub-samples of Compustat. The coverage is all those firms who have records of participating as a customer or supplier following Financial Accounting Standards Rule No. 131. The (Defense Sales / Sales) ratio is defined as the total value of Department of Defense (DoD) procurement contracts divide by Compustat firm Sales (mnemonic SALE)

Table 2: Changes in DoD Spending and Product Market Concentration, 1976-2003.

Dependent Variable	(1) $\Delta\ln(D^L)_{lt}$	(2) $\Delta\ln(D^L)_{lt}$	(3) $\Delta\ln(D^L)_{lt}$
$(\text{Herfindahl})_{t-2}$	-0.087		
	(0.092)		
$(\text{Herfindahl})_{t-5}$		-0.061	
		(0.059)	
$(\text{Herfindahl})_{t-10}$			-0.024
			(0.066)
1-Digit Trends	Yes	Yes	Yes
Number of Product Groups	154	154	154
Number of Observations	3353	3353	3353

Notes: Standard errors clustered by 2-digit product category in parentheses. The data is a 2-digit product level panel of NARA procurement data. The dependent variable is the log 1-year change in the total amount of procurement spending at the 2-digit level. The Herfindahl index is calculated as the sum of the squared market shares for the top 50 contractors in each 2-digit product group. There are 34 1-digit groups with a trend term included for each group.

Table 3: Direct Effects of Defense Sales for Customers, 1976-2003.

	(1) log(Sales)	(2) log(Patent Count)	(3) log(Cites)	(4) log(R&D)
(A) OLS Estimates				
log(Defense Sales)$_{t-1}$	0.040***	0.039***	0.070***	0.032***
	(0.005)	(0.007)	(0.011)	(0.006)
(B) IV Estimates				
log(Defense Sales)$_{t-1}$	0.070***	0.084***	0.167***	0.057***
	(0.011)	(0.015)	(0.023)	(0.015)
(C) First Stage				
log(Defense Market Size)$_{t-1}$	0.262***	0.262***	0.262***	0.167***
	(0.016)	(0.016)	(0.016)	(0.023)
F-Statistic	1457.3	1457.3	1457.3	922.1
Number of SIC4 industries	272	272	272	193
Number of Firms	1,238	1,238	1,238	940
Number of Observations	20,327	20,327	20,327	13,122

Notes: Standard errors clustered by firm in parentheses. All specification include SIC4-year fixed effects. "Defense Sales" represents the value of all of the defense procurement contracts directly received by a firm. Note that the first stage specification is common by construction for the sample in the first three columns. The instrument "Defense Market Size" is defined as the firm-product weighted Department of Defense (DoD) market size for a firm. That is, total spending by the DoD per 2-digit federal supply code category multiplied by the within-firm portfolio share of the product (with shares calculated using a 5-year lag).

Table 4: Cascade Effects for Suppliers, 1976-2003.

	(1) log(Sales)	(2) log(Patent Count)	(3) log(Cites)	(4) log(R&D)
(A) Baseline				
log(Cascade Defense Sales)$_{t-1}$	0.018***	0.011***	0.016**	0.020***
	(0.004)	(0.004)	(0.006)	(0.004)
log(Direct Defense Sales)$_{t-1}$	0.045***	0.026***	0.045***	0.025***
	(0.005)	(0.004)	(0.007)	(0.005)
(B)Plus SIC4-Year Controls				
log(Cascade Defense Sales)$_{t-1}$	0.021***	0.012***	0.019***	0.019***
	(0.004)	(0.004)	(0.007)	(0.005)
log(Direct Defense Sales)$_{t-1}$	0.044***	0.025***	0.045***	0.027***
	(0.006)	(0.005)	(0.007)	(0.006)
Number of SIC4 industries	300	300	300	300
Number of Firms	2,584	2,584	2,584	2,206
Number of Observations	33,241	33,241	33,241	23,907

Notes: Standard errors clustered by firm in parentheses. "Cascade Defense Sales" represents the accumulated transmission of a directly-received defense contracts at the customer-level through to suppliers. This is accumulated across four iterated rounds of customer-supplier linkages. "Direct Defense Sales" represents defense contract dollars directly received by a supplier. The baseline specification in panl (a) includes SIC2-year fixed effects.

Table 5: IV Estimates of Cascade Effects for Suppliers, 1976-2003.

	(1) log(Sales)	(2) log(Patent Count)	(3) log(Cites)	(4) log(R&D)
(A) OLS Estimates				
log(Cascade Defense Sales)$_{t-1}$	0.021***	0.012***	0.019***	0.019***
	(0.004)	(0.004)	(0.007)	(0.005)
(B) IV Estimates				
log(Cascade Defense Sales)$_{t-1}$	0.027***	0.013***	0.028***	0.019***
	(0.005)	(0.004)	(0.008)	(0.006)
(C) First Stage				
log(Cascade Market Size)$_{t-1}$	0.609***	0.609***	0.609***	0.596***
	(0.010)	(0.010)	(0.010)	(0.011)
F-Statistic	3833.4	3833.4	3833.4	3044.2
Number of SIC4 industries	300	300	300	300
Number of Firms	2,584	2,584	2,584	2,206
Number of Observations	33,241	33,241	33,241	23,907

Notes: Standard errors clustered by firm in parentheses. All specification include SIC4-year fixed effects. Note that the first stage specification is common by construction for the sample in the first three columns. The instrument "Cascade Market Size" is defined as the accumulated transmission of changes in the customer-level DoD 'firm-specific market-size' through to suppliers. This is accumulated across four iterated rounds of customer-supplier linkages.